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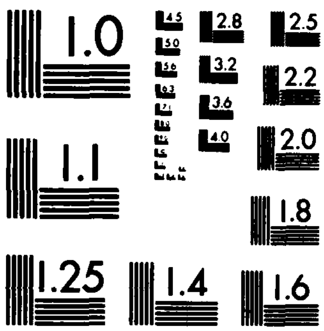

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Inductive Information Retrieval Using Parallel Distributed Computation

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Abstract

Massively parallel, distributed models of computation offer a new approach to the representation and manipulation of knowledge. This paper reports on an application of parallel models to the area of information retrieval. The retrieval system described makes dynamic use of the internal structure of a database to infer relationships among items in the database. Using these relationships, the system can help overcome incompleteness and imprecision in requests for information, as well as in the database itself.

Inductive Information Retrieval Using Parallel Distributed Computation

Massively parallel models of computation have shown promising results in the areas of pattern recognition, memory, learning, and language comprehension (Anderson & Hinton, 1981; Feldman & Ballard, 1982; McClelland & Rumelhart, 1981; McClelland, Rumelhart, & Hinton, in preparation). These models, called *connectionist* or *parallel distributed processing* (*PDP*) models, offer a new approach to the representation and manipulation of knowledge. In this approach, computation takes place through the simultaneous interaction of many small pieces of knowledge, some pieces supporting each other and other pieces competing with each other. PDP models have demonstrated the kind of flexibility and computational power that characterize cognition, particularly those aspects of cognition that people perform so effortlessly and naturally. The PDP approach promises to be particularly useful in areas that demand flexible inferencing and reasoning with incomplete or imprecise information (which I call *inductive reasoning*). This paper reports on an application of the PDP approach to one such area, information retrieval.

I will focus on information retrieval systems used in bibliographic search, known as document retrieval systems. Although document retrieval will serve as the primary example of this paper, the discussion generalizes quite readily to information retrieval of all sorts. Indeed, the PDP conceptualization has been applied to information retrieval tasks as diverse as locating files and specifying commands on a computer system (Greenspan & Smolensky, 1984) and organizing information in an on-line manual (O'Malley, Smolensky, Bannon, Conway, Graham, Sokolov, & Monty, 1983).

I begin with a discussion of document retrieval and argue that inductive reasoning is useful in document retrieval, then present a PDP retrieval model and examine its properties.

Document Retrieval

Document retrieval systems are typically used to search for books or articles (hereafter, *documents*) on a particular topic. To aid in this process, each document is labeled by a set of *descriptor terms* that characterize the content matter of the document. For example, a book on Pascal compiler design might be identified by the descriptors PASCAL, COMPILERS, COMPUTING, PROGRAMMING, and LANGUAGES. Queries to such a system often take the form of a Boolean expression of descriptors, and the system reports all documents satisfying the expression. For example, one might request all documents about "PROGRAMMING AND (COMPILERS OR INTERPRETERS)."

There are two difficult problems with such a system. First, users have a hard time accurately specifying the information they are seeking, possibly because the document descriptors have different semantics than they realize, or because they fail to include relevant descriptors in the query, or because they include irrelevant descriptors. The end result is that the set of descriptors chosen for the query is semantically inaccurate or ill-specified. The second

problem with document retrieval systems is that the indexing of documents is itself often inconsistent and incomplete. Relevant descriptors are sometimes omitted from a document, and because documents are added to the collection over long periods of time by many individuals, indexing is often inconsistent. When either query or document descriptors are faulty, traditional retrieval systems generally perform poorly because the retrieval process is too literal minded; it simply matches query descriptors against document descriptors.

Rather than assuming that the query is a precise specification of the user's intentions and that the document descriptors precisely characterize the documents, a retrieval system might better assume that there is some uncertainty in the query and document descriptors and that the descriptors can be interpreted in a loose sense. Under these assumptions, the retrieval process must be considered inductive, not deductive.

What sort of output will an inductive retrieval system produce? The deductive Boolean retrieval system described above produced a set of documents that matched the query exactly; all other documents were rejected. However, an inductive system will, by its very nature, tend to produce a set of documents that match the query to varying degrees. Thus, an inductive system will require a procedure for assigning a quality of match, or *relevance measure*, to each document given a particular query.

There are a variety of methods in the information retrieval literature for assigning a relevance measure to a document (Bärtschi & Frei, 1982; Bookstein, 1980; Buell & Kraft, 1981; Salton, Fox, & Wu, 1983). Some use fuzzy logics to evaluate Boolean queries; others, known as *vector models*, treat documents and queries as vectors in a concept space of large dimensionality and then compute the distance between vectors. However, all of these methods base their judgments of relevance solely on the relationship between document descriptors and query descriptors.

On first thought, there doesn't seem to be any other information on which to base a judgment of relevance. However, the PDP retrieval model proposed below exploits an additional source of information: the internal structure of the database. This structure allows the model to dynamically determine the relationship between two documents or two descriptors, and to use this information in computing a relevance measure.

The PDP Retrieval Model

To understand the retrieval model, it may be useful first to outline the class of PDP models. These models consist of a large number of simple processing units operating in parallel. In most cases, each unit represents a possible hypothesis. Units have varying degrees of confidence in the truth of their hypotheses. The degree of confidence is quantified by an internal state variable of the unit, its *activation level*. Units can transmit their activation levels to one another through connecting links. There are two types of links: excitatory and inhibitory. When two units represent mutually compatible hypotheses, they will be connected by an excitatory link. Excitatory links cause the confidence in one hypothesis to increase the confidence in the other hypothesis. When two units represent mutually incompatible hypotheses, they will be connected by an inhibitory link. Inhibitory

links cause the confidence in one hypothesis to decrease the confidence in the other hypothesis. The outcome of any computation in a PDP model is thus the result of cooperation and competition among a large number of simple processes.

In the PDP retrieval model, each document and each descriptor is represented by a unit. Figure 1 shows a portion of a PDP system, with the upper row of units representing documents and the lower row descriptors. The activation level of a document unit indicates the system's belief in the relevance of the document, i.e., the relevance measure. Large activation levels indicate a high degree of relevance; low or negative activation levels indicate irrelevance. The system decides on the relevance of descriptors as well as documents. Like the documents, the relevance of a descriptor is indicated by its activation level.

Links connecting units permit the flow of activation. Mutually excitatory links connect each document and all descriptors associated with the document. Thus, evidence for a particular descriptor is evidence for all documents associated with it; and evidence for a particular document is evidence for all of its descriptors. Furthermore, there are mutually inhibitory links between every pair of documents. Thus, evidence for one document is counterevidence for all others.

The dynamics of the model are based on McClelland and Rumelhart's (1981; Rumelhart & McClelland, 1982) interactive activation model of word perception. A formal statement of the activation rules and parameter values used to implement the model are included in the Appendix. In simulating the model, time is quantized into discrete steps, and the following sequence of events occurs during each time step. If a unit has a positive activation level, it passes its activation through each of its links; otherwise, no activation is passed. Each unit computes the sum of its incoming activations, weighted by connection strengths associated with each link. This net input, modulated by the current unit activity (in order to prevent the unit's activity from exceeding a certain maximum or minimum level), is added to the current activity. Finally, a unit loses a fixed percentage of its activation during each time step, resulting in an exponential decay of activation over time. The system stabilizes when the net increase in activation to each unit equals the net decrease, that is, when the excitatory input exactly matches the combination of inhibitory input and decay. In the implementation to be described, the system approached equilibrium within about 25 time steps.

Querying the model involves activating a set of descriptor units and seeing which document units become active as a result. In contrast to the Boolean queries described earlier, the PDP-model query merely specifies a set of relevant descriptors. The set includes both positive and negative descriptors, the positive descriptors being those that should be associated with the retrieved documents and the negative descriptors those that should not. The activation levels of the positive-descriptor units are clamped to the maximum allowed level and the negative-descriptor units to the minimum allowed level. The activation levels of these units remain clamped throughout the course of processing and are not affected by decay or incoming activations.

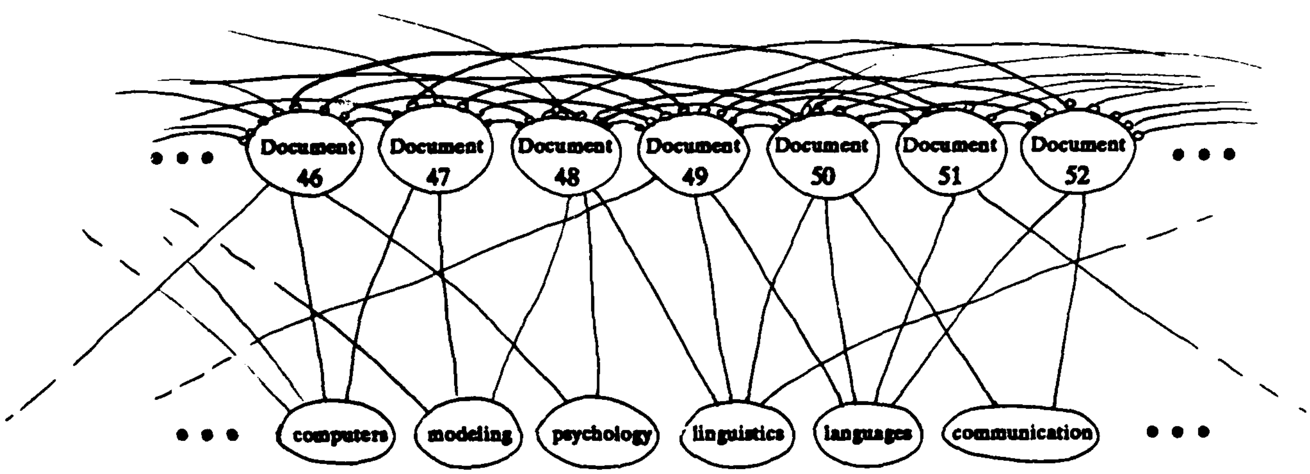

Figure 1. A portion of a PDP document retrieval system.

At an abstract level of description, the system operates as follows. The user activates a set of descriptors. These descriptors activate a set of documents. The documents in turn activate new descriptors, which will activate some new documents as well as reinforce the activation of already active documents, and so on. Activation continually flows from descriptors to documents and vice-versa. This flow of activation allows descriptors in a query to indirectly suggest other descriptors that may be useful in the document search, and it allows active documents to indirectly suggest other documents.

Implementation and Testing of the Model

A retrieval system was developed that constructs a PDP network representation of a database given to it, allows the user to activate sets of descriptor units, and displays documents ranked by activation level. The system includes a graphics interface that shows the activity of all documents and descriptors.

The document collection used to examine the system consisted of books and articles belonging to a graduate student in our lab. The collection had 407 documents, was indexed by 133 descriptors, and had an average of 3.4 descriptors per document. It had been built up over the course of several years. Indexing of the documents had been performed as the documents were added. Consequently, the indexing was somewhat inconsistent. All retrieval examples given in the next section come from this collection.

Properties of the Model

Compensation for Inaccuracy and Incompleteness in the Query

During the course of processing, an active descriptor may cause other descriptors to become active. The retrieved set of documents will be ones that match either the descriptors that were initially active (the query descriptors) or the internally activated descriptors (the *induced descriptors*). For example, consider what happens when the descriptor LINGUISTICS in Figure 1 is activated. Documents 48, 49, and 50 will become active, and each will begin activating its own descriptors; LANGUAGES will thus be activated by documents 49 and 50. Next, LANGUAGES will activate its documents, sending some activation back to documents 49 and 50, but also activating documents 51 and 52. Thus, documents 51 and 52 become active not because their descriptors were specified in the query, but because the system saw one of their descriptors as being related to descriptors in the query. In the document collection used as a testbed, the descriptors LOGIC and REASONING also became slightly active after LANGUAGES did, presumably because these two descriptors are related to LANGUAGES in the same way that LANGUAGES is related to LINGUISTICS. In essence, the system has added LANGUAGES, and to a lesser extent LOGIC and REASONING, to the list of query descriptors.

One descriptor tends to activate another to the extent that the two descriptors co-occur in the currently active subset of the document collection. The tendency for one descriptor to activate another is thus influenced by the other descriptors that are active, because the other active descriptors affect which subset of the collection is active. As an example of this context dependency, if LANGUAGES is activated along with COMPUTERS, the

descriptors PROGRAMMING, AI, and DESIGN become strongly active, whereas if LANGUAGES is activated along with PSYCHOLOGY, then COGNITIVE and LINGUISTICS become active.

Clearly, the model achieves a flexible interpretation of the query. The query is used as a guide in the retrieval process, steering the model's attention in certain directions, not as a rigid criterion that must be matched exactly. This flexibility allows the system to help compensate for inaccurate and incomplete queries.

Compensation for Inconsistency and Incompleteness in the Indexing of the Document Collection

When a document has many descriptors in common with the set of active documents, the document is likely to become active itself, even if it doesn't match the query very well. This property is quite useful if descriptors are accidentally omitted in the indexing of a document. For example, one might suppose that documents 51 and 52 in Figure 1 should have been indexed with the descriptor LINGUISTICS, because many items that concern LANGUAGES also concern LINGUISTICS. The system will make precisely this inference when LINGUISTICS is activated via the induced descriptor mechanism described above.

Thus, the system can help to overcome inconsistency and incompleteness in the indexing of the collection. Of course, the performance of the system degrades with a degradation in indexing, but because of the system's statistical nature, the degradation in performance is gradual.

Ranking of the Retrieved Documents

The activation level of a document is a measure of its relevance according to the model, with the most active documents being most relevant. Thus, ranking the retrieved documents according to their activation levels will produce a set ordered by relevance. The ordered set is quite useful when many documents are retrieved, because it suggests which documents to inspect first.

Let's examine what the ranked set of documents will look like. With the parameter values indicated in the Appendix, there will be a very strong tendency for documents matching the query exactly to be most active, followed by partial matches, followed by documents having no descriptors in common with the query but having at least one active (induced) descriptor. Conventional relevance measures cannot distinguish among the exact matches, and can make only coarse-grain distinctions among the partial matches. This is because these relevance measures are based solely on the query descriptors. However, the PDP model also uses the induced descriptors to form its relevance measure. Thus, two documents that share the same query descriptors may nonetheless be assigned different relevance measures.

Consider what happens when several documents in the collection match the query exactly, as when LANGUAGES is queried in Figure 1. Documents 49 through 52 will immediately become active, all to the same extent. Documents 49 and 50 will then support LINGUISTICS, and documents 50 and 52 COMMUNICATION. These two descriptors will in turn support

their respective documents, with document 50 receiving support from both. Thus, document 50 becomes the most active.

The most active document within the set of exact matches is the one with the greatest number of highly active induced descriptors; documents with successively less activation have fewer such descriptors. Because the induced descriptors are derived from their association with many of the active documents, one may conclude that the most active documents are those that share many descriptors with the other active documents. In this sense, the most active documents are those most *representative* or *prototypical* of the retrieved set. A representative document may serve as a useful example if a query produces a large retrieval set.

Consider now the meaning of representativeness when no document matches the query exactly but there are many partial matches. For example, this is the case in the test section when a query is made for LEARNING and PROGRAMMING. Documents indexed by the descriptor pairs LEARNING and COMPUTERS, or PROGRAMMING and PSYCHOLOGY, end up with higher activation levels than those indexed by LEARNING but not COMPUTERS, or PROGRAMMING but not PSYCHOLOGY. The first subset is most representative of the retrieval set as a whole, and is clearly a better match to the query than the second. However, conventional relevance measures are unable to make the distinction between these two subsets.

Providing Cues for Continued Search

Information retrieval can be thought of as an iterative process (Tou, Williams, Fikes, Henderson, & Malone, 1982). The user first formulates a rough query, and in successive retrieval attempts the query is reformulated. The induced descriptors may be helpful in reformulating the query. Because these descriptors are associated with many of the retrieved documents, they are useful for partitioning the retrieval set. That is, if the user can state that a certain descriptor should or should not be present among the retrieved documents, the size of the retrieval set can be reduced. The descriptors carrying the most information are those associated with exactly half the retrieval set. Roughly, this is characteristic of the induced descriptors with highest activity.

Retrieval by Example

A query may be formulated using documents instead of descriptors, thus allowing the user to request documents that are similar to a given set of documents. Similarity is measured in terms of common descriptors. For example, if documents 47 and 50 are activated in Figure 1, document 48 is also likely to become activated via the descriptors it shares with documents 47 and 50.

Parameters of the Model

The model has over a dozen parameters (some of which have been removed from the Appendix to simplify the presentation), many more if one considers varying connection strengths for each link. Overall, it was surprising how robust the basic properties of the model were under variation in these parameters. However, several parameters are useful in controlling the behavior of the model. These parameters affect the model's behavior as follows.

Document-Document Inhibition ($w_{D_k D_i}$) and Descriptor Decay Rate (θ_D)

These parameters control how freely the model associates. If $w_{D_k D_i}$ or θ_D are large, activation cannot easily be passed through the system, and the model will tend to retrieve only documents indexed by one or more of the query descriptors; if sufficiently large, the model will behave exactly like a vector model (described in the section on Document Retrieval and in Salton, Fox, & Wu, 1983). Conversely, if these parameters are small, positive feedback reverberates throughout the model and it "hallucinates"; internal activations begin to dominate external (query) activations. To avoid hallucinatory behavior, these parameters are set so that induced descriptors never approach the activation level of the query descriptors.

Document-to-Descriptor and Descriptor-to-Document Connection Strengths ($w_{D_i d_j}$ and $w_{d_j D_i}$)

These parameters control the strength of association between a document and a descriptor. Some descriptors may be more important in characterizing a document than others, and this could be reflected in the connection strengths.

Resting Activation Levels

In the current implementation, all document units have resting activation levels of zero, that is, their activity decays back to zero. The resting activation levels can be adjusted, however, to bias retrieval in favor of certain documents. Suppose that the resting activation level of a document corresponded to its frequency of activation over long periods of time. Then documents that a user retrieved often would be retrieved more readily.

Query Descriptor Activation

Query descriptors can be assigned different levels of activation to vary their relative importance in the query. The activation levels can be set automatically (e.g., using inverse document frequency, as described by Sparck Jones, 1973) or directly by the user.

Document and Descriptor Fan-in Exponents (α_D and α_d)

These parameters help compensate for a bias built into the system. To see the bias, consider a query of MODELING in Figure 1. Documents 47 and 48 will become activated, followed by descriptors COMPUTERS, PSYCHOLOGY, and LINGUISTICS. A positive feedback loop is formed between these documents and their associated descriptors. Assuming activation of the descriptors from other sources is small, document 47 will become slightly less active than document 48, simply because it is associated with fewer descriptors. Thus, positive feedback loops bias activation in favor of documents associated with many descriptors; they do similarly for descriptors associated with many documents.

One solution to this dilemma is to replace each descriptor unit with a dipole, one unit of the dipole representing the descriptor and the other its complement. Connections would be made between each document and one of the two dipole units. Thus, all descriptors would receive an equal number of inputs, as would all dipoles, causing the bias to disappear. However, this solution requires a massive interconnection of documents and dipoles.

An inexact but practical solution is to base the connection strength of links coming into a unit on the number of incoming links. The more links a unit has, the less activity each link can provide. This solution has been implemented using α_D and α_d. These parameters were adjusted until the bias was approximately nullified.

Evaluating the Model

The best support for the model lies in its ability to produce surprising results, often retrieving documents that have no descriptors in common with the query yet are clearly relevant. These are documents that no conventional deductive retrieval system could find. It is difficult to draw firm conclusions as to the model's utility, because systematic data evaluating the model's performance has yet to be collected. However, the model has been tested on two other databases, one of operating-system commands and the other of local restaurants, [1] and the model performs well on both.

Several drawbacks of the model should be noted. First, queries lack the expressive power of a Boolean query formulation; no distinction is made between "and" and "or." This problem is inherent in all vector models (Salton, Fox, & Wu, 1983). Second, running the model on serial hardware in real time with a large database may be difficult. Third, the model requires that the documents be indexed by a highly overlapping and preferably correlated set of descriptors. Without such an indexing scheme, there is no internal structure to

1. In the restaurant database, restaurants were described by their nationality, location, and cost. Because restaurants have only one value for each of these parameters, the co-occurrence of descriptors could not be used to infer, say, that GREEK restaurants are somewhat similar to ARMENIAN restaurants, or that a restaurant in NORTH PARK is similar to one in HILLCREST. Consequently, it was necessary to specify the semantics of the descriptors explicitly. Descriptor semantics were built into the PDP system by linking related descriptors with a strength of connection corresponding to the degree of association of the descriptors. For example, the GREEK descriptor unit was linked to the ARMENIAN unit, but not to the JAPANESE unit.

the database, and the model performs exactly like a vector model (Salton, Fox, & Wu, 1983).

Conclusions

This paper has presented a new area of application for parallel distributed computation. Although evaluation has been informal, the PDP approach to information retrieval seems potentially powerful and robust. At very least, the PDP approach has pointed out that the internal structure of a database can be a useful source of knowledge in retrieval. A stronger claim, however, is that the PDP approach assists users of a retrieval system in tracking down relevant information, particularly when either the query or the database is incomplete or imprecise. The assistance provided is threefold. First, a PDP retrieval system is able to flexibly interpret descriptors in the query and the database. Second, the system ranks retrieved information precisely and in order of presumed relevance to the user. Third, the system suggests directions that users may take to further specify their query.

Appendix - Summary of Activation Rules and Parameter Values of the Test System

The activity level of document unit i at time $t+1$ is given by

$$D_i(t+1) = \begin{cases} (1-\theta_D)\, D_i(t) + \eta_{D_i}(t)\,(M - D_i(t)) & \text{if } \eta_{D_i}(t) > 0 \\ (1-\theta_D)\, D_i(t) + \eta_{D_i}(t)\,(D_i(t) - m) & \text{if } \eta_{D_i}(t) \leq 0 \end{cases}$$

where $\eta_{D_i}(t)$ is the net input to document i at time t, as given by

$$\eta_{D_i}(t) = (\bar{c}_D / c_{D_i})^{\alpha_D} \sum_{j=1}^{n_d} w_{d_j D_i} U(d_j(t)) \; - \; \sum_{k=1}^{n_D} w_{D_k D_i} U(D_k(t)).$$

The activity level of descriptor unit j at time $t+1$ is given by

$$d_j(t+1) = \begin{cases} (1-\theta_d)\, d_j(t) + \eta_{d_j}(t)\,(M - d_j(t)) & \text{if } \eta_{d_j}(t) > 0 \\ (1-\theta_d)\, d_j(t) + \eta_{d_j}(t)\,(d_j(t) - m) & \text{if } \eta_{d_j}(t) \leq 0 \end{cases}$$

where $\eta_{d_j}(t)$ is the net input to descriptor j at time t, as given by

$$\eta_{d_j}(t) = (\bar{c}_d / c_{d_j})^{\alpha_d} \sum_{i=1}^{n_D} w_{D_i d_j} U(D_i(t)).$$

$U(x)$ is the zero-threshold identity function:

$$U(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ x & \text{if } x > 0. \end{cases}$$

All other quantities are parameters of the document collection or are constants (the values in parentheses are those used in the test system):

n_D	number of documents in the collection
n_d	number of descriptors in the collection
$w_{d_j D_i}$	strength of connection from descriptor j to document i (0 if no connection; .10 otherwise)
$w_{D_i d_j}$	strength of connection from document i to descriptor j (0 if no connection; .03 otherwise)
$w_{D_k D_i}$	strength of (inhibitory) connection from document k to document i (0 if $k=i$; .0075 otherwise)
θ_d	descriptor decay rate (.25)
θ_D	document decay rate (.10)
M	maximum activity level (1.0)
m	minimum activity level (-0.2)
c_{D_i}	number of descriptors in document i
c_{d_j}	number of documents indexed under descriptor j
$\bar{c}_D$	average number of descriptors per document in collection
$\bar{c}_d$	average number of documents per descriptor in collection
α_D	document fan-in exponent (.10)
α_d	descriptor fan-in exponent (.30)

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ONR-8403. Paul Smolensky and Mary S. Riley. *Harmony Theory: Problem Solving, Parallel Cognitive Models, and Thermal Physics*. April 1984. The first two papers will appear in *Proceedings of the Sixth Annual Meeting of the Cognitive Science Society*, Boulder, CO, 1984.

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ONR-8405. Michael C. Mozer. *Inductive Information Retrieval Using Parallel Distributed Computation*. May 1984.

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8301. David Zipser. *The Representation of Location.* May 1983.

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8403. Steven L. Greenspan. *Reference Comprehension: A Topic-Comment Analysis of Sentence-Picture Verification*. April 1984.

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